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RECURSIVE MOMENT FORMULAS FOR REGENERATIVE SIMULATION

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TECHNICAL REPORT NO. 5

October 1984

Prepared under the Auspices

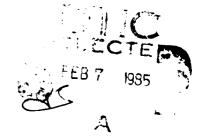
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DAAG29-84-K-0030

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*This research was also partially supported under National Science Foundation Grant MCS-8203483

RECURSIVE MOMENT FORMULAS FOR REGENERATIVE SIMULATION

by

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1. Introduction

Let f be a real-valued function defined on the state space of a regenerative process $X = \{X(t) : t \ge 0\}$ with regeneration times $0 = T_0 < T_1 < \cdots$, and suppose that

(1.1)
$$r_{t} = \frac{1}{t} \int_{0}^{t} f(X(s))ds + r \quad a.s.$$

as $t \to \infty$. The problem of estimating r via a simulation of X is called the steady state simulation problem.

Relation (1.1) implies that r_t is a strongly consistent point estimator for r. To obtain confidence intervals for r, set (for $k \ge 1$)

$$Y_{k}(f) = \int_{T_{k-1}}^{T_{k}} f(X(s))ds$$

$$T_{k-1}$$

$$T_{k} = T_{k} - T_{k-1}$$

$$T_{k} = Y_{k}(f) - r\tau_{k}$$

$$T_{k} = T_{k-1}$$

$$T_{k} = T_{$$

The regenerative structure of X guarantees that $r = E\{Y_1(f)\}/E\{\tau_1\}$ and that $\{(Y_k(f), \tau_k) : k \ge 1\}$ is a sequence of i.i.d. random vectors. Standard arguments (see CRANE and IGLEHART (1975)) show that if $E\{Y_1^2(f) + \tau_1^2\} < \infty$, then

(1.2)
$$\sqrt{t}(r_t - r) \Rightarrow \sigma N(0,1)$$

as $t \to \infty$, where $\sigma^2 = \sigma^2\{Z_1\}/E\{\tau_1\}$. To use (1.2) for confidence intervals, the regenerative cycle structure of **X** is exploited to obtain a strongly consistent estimator v_t for σ^2 .

These confidence intervals, while asymptotically correct, often have poor small-sample behavior. For example, such confidence intervals often tend to significantly undercover the parameter r. Several recent studies have examined this problem. GLYNN (1982), in considering regenerative confidence intervals on the time scale of regenerative cycles, obtained asymptotic expansions for the coverage error which indicated that skewness/kurtosis effects play a significant role in determining quality of the confidence interval. To be more precise, the error, to a first approximation, is determined by the magnitude of quantities of the form $\mathbb{E}\{Z_1^m \ \tau_1^n\}$ for $m+n\leq 4$. GLYNN and IGLEHART (1984) obtain expressions for the asymptotic covariance between r_t and v_t , and the variance of v_t ; these expressions also involve mixed moments of the form $\mathbb{E}\{Z_1^m \ \tau_1^n\}$. Consequently, in studying small-sample behavior of regenerative confidence intervals, it is of some interest to be able to calculate the exact values of the mixed moments for some "test case" stochastic models. HORDIJK,

IGLEHART, and SCHASSBERGER (1976) showed how to do this for $m+n \le 2$, when X is a discrete or continuous time Markov chain with countably many states. In this note, we show how to calculate such quantities when X is a semi-Markov process with countably many states; discrete and continuous time Markov chain results follow as special cases.

2. Statement of the Recursive Moment Formulas

Let $X = \{X(t) : t \ge 0\}$ be an irreducible non-explosive regenerative semi-Markov process on countable state space E. Thus, X(t) may be represented as

$$X(t) = \sum_{k=0}^{\infty} R_k I(S_k \le t < S_{k+1})$$
,

where:

- (i) $R = \{R_n : n \ge 0\}$ is a discrete-time Markov chain on E with transition matrix $P = (p_{xy} : x, y \in E)$
- (ii) $S = \{S_n : n \ge 0\}$ is an increasing sequence of jump times with $S_0 = 0$ and differences $\alpha_n = S_{n+1} S_n$ which are conditionally independent r.v.'s given R.

The conditional distribution of α_n is given by $F(R_n,R_{n+1},dt) = P(\alpha_n \in dt | \mathbb{R})$, where F(x,y,0) = 0 for all $x,y \in \mathbb{R}$. Note that $S_n + \infty$ a.s., since \mathbb{X} is non-explosive by assumption. Fix $z \in \mathbb{R}$ as the regenerative state; let $T(z) = \inf\{t > 0 : X(t-) \neq z, X(t) = z\}$ and set

$$Y(u) = \int_{0}^{T(z)} u(X(t))dt$$

where $u : E \rightarrow R$ is an arbitrary function. We wish to study mixed moments of the form

$$a_{ij}(x) = E_{x}(Y(g)^{i} Y(h)^{j})$$

for $x \in E$, $0 \le i \le m$, and $0 \le j \le n$, when g and h are fixed functions, and m and n are non-negative integers. Throughout the paper we shall use $P_X\{\cdot\}$ and $E_X\{\cdot\}$ to denote conditional probabilities and expectations, given $X(0) = R_0 = x$. Note that by choosing $g(\cdot) = f(\cdot) - r$ and $h(\cdot) = 1$, $a_{i,j}(z)$ yields $E_Z\{z_1^i, \tau_1^j\}$.

To state our result, let a \vee b denote $\max(a,b)$ and set $b_{\min}(x) = E_{\chi}(\{Y(|g|) \vee 1\}^{m} (\{Y(|h|) \vee 1\}^{n})$. Let G_{n} and β_{n} be the matrix and function, respectively, defined by

$$G_{n}(x,y) = \begin{cases} p_{xy} \mu_{n}(x,y) ; & y \neq z \\ 0 ; & y = z \end{cases}$$

$$\beta_n(x) = \sum_{y \in E} \mu_n(x,y) p_{xy}$$

where $\mu_n(x,y) = \int_0^\infty t^n \ F(x,y,dt)$. Also, we shall identify real-valued functions $u(\cdot)$ on E with column vectors \mathbf{u} , and shall use the notation $\mathbf{u} \circ \mathbf{v}$ to denote the vector with \mathbf{x}^{th} component $(\mathbf{u} \circ \mathbf{v})(\mathbf{x}) = \mathbf{u}(\mathbf{x})\mathbf{v}(\mathbf{x})$. Set $\mathbf{u}^0(\cdot) = 1$ and $\mathbf{u}^{n+1} = (\mathbf{u} \circ \mathbf{u}^n)$ for $n \geq 0$.

Let $\mathcal C$ denote the class of all $m \times n$ matrix-valued functions, $\mathcal C$, on $\mathcal E$. Then set

$$\min = \left\{ \mathbf{C} \in C : \sum_{\mathbf{k}=0}^{\mathbf{i}} \sum_{\ell=0}^{\mathbf{j}} |g(\mathbf{x})|^{\mathbf{i}-\mathbf{k}} \cdot |h(\mathbf{x})|^{\mathbf{j}-\ell} \right.$$

$$\cdot \sum_{\mathbf{y} \in E} G_{\mathbf{i}+\mathbf{j}-\mathbf{k}-\ell}(\mathbf{x},\mathbf{y})|c_{\mathbf{k}\ell}(\mathbf{y})| < \infty$$

$$\text{and } (G_0^{\mathbf{k}} c_{\mathbf{i}\mathbf{j}})(\mathbf{x}) + 0 \text{ as } \mathbf{k} + \infty ,$$

$$\text{for all } \mathbf{x} \in E, \ 0 \le \mathbf{i} \le \mathbf{m}, \text{ and } 0 \le \mathbf{j} \le \mathbf{n} \right\} .$$

(2.1) Theorem. If $b_{mn}(z) < \infty$, then $A = \{a_{ij} : 0 \le i \le m, 0 \le j \le n\}$ is the unique solution in C_{mn} to the system:

$$(2.2) \ \mathbf{e_{ij}} = \mathbf{g^{j}} \circ \mathbf{k^{j}} \circ \beta_{i+j} + \sum_{(k,l) \in B_{ij}} \binom{i}{k} \binom{j}{l} (\mathbf{g^{i-k}} \circ \mathbf{k^{j-l}} \circ \mathbf{G^{i+j-k-l}} \mathbf{e_{k,l}}),$$

where $0 \le i \le m$, $0 \le j \le n$, and $B_{ij} = \{(k,l) : 0 \le k \le i, 0 \le l \le j, k+l > 0\}$.

Set $\tau = \inf\{n \ge 1 : R_n = z\}$ and observe that

$$G_0^k(x,y) = P_x\{R_k = y, \tau > k\}$$
.

Hence, $\mathbf{G}_0^{\mathbf{k}} \to 0$ as $\mathbf{k} \to \infty$. It follows that if E has a finite number of elements, $C_{\min} \equiv C$, so that the \mathbf{a}_{ij} 's are unique in the class of all possible solutions to (2.2). Also, in the presence of a finite state space, it is well known that $(\mathbf{I} - \mathbf{G}_0)^{-1}$ exists, so that (2.2) may be re-written as

(2.3)
$$e_{ij} = (I - C_0)^{-1} \{ g^i \circ w^j \circ \beta_{i+j} .$$

$$+ \sum_{(k,l) \in A_{ij}} {i \choose k} {i \choose l} (g^{i-k} \circ w^{j-l} \circ (C_{i+j-k-l} e_{k,l})) \} ,$$

where $0 \le i \le m$, $0 \le j \le n$, i + j > 0, and $A_{ij} = \{(k, l) : 0 \le k \le i$, $0 \le l \le j$, $0 < k + l < i + j\}$. Also observe that $c_{00} \equiv l$. Note that the system of equations (2.3) is recursive in i + j, in the sense that the c_{ij} 's may be solved in terms of the c_{kl} 's, where k + l < i + j. By successively solving for the c_{kl} 's with fixed k + l on each iteration, one eventually obtains c_{mn} .

Formula (2.3) can be further simplified when X has special structure. Note that if X is a continuous time Markov chain, then

$$F(x,y,dt) = \lambda(x) \exp(-\lambda(x)t)dt$$

for t > 0, so that

$$\mu_n(x,y) = n!/\lambda(x)^n \equiv \eta_n(x) .$$

We find that (2.3) can be re-written as

$$\begin{split} \mathbf{e}_{ij} &= (\mathbf{I} - \mathbf{G}_0)^{-1} \{ \mathbf{g}^i \circ \mathbf{h}^j \circ \eta_{i+j} \\ &+ \sum_{(k,l) \in A_{ij}} {i \choose k} {i \choose l} (\mathbf{g}^{i-k} \circ \mathbf{h}^{j-l} \circ \eta_{i+j-k-l} \circ \mathbf{G}_0 \in \mathbb{R}^l) \} \;, \end{split}$$

where $0 \le i \le m$, $0 \le j \le n$, and i+j > 0.

For discrete time Markov chains, $\beta_n \equiv 1$ and $G_n = G_0$, so (2.3) takes the form

$$\begin{split} \mathbf{e}_{ij} &= (\mathbf{I} - \mathbf{G}_0)^{-1} \{ \mathbf{g}^i \circ \mathbf{h}^j \\ &+ \sum_{(k,l) \in A_{ij}} \binom{i}{k} \binom{j}{l} (\mathbf{g}^{i-k} \circ \mathbf{h}^{k-l} \circ (\mathbf{G}_0 \ \mathbf{e}_{kl})) \} \ , \end{split}$$

where $0 \le i \le m$, $0 \le j \le m$, and i+j > 0.

Relation (2.4) expresses $\mathbf{c_{ij}}$ in terms of $\mathbf{G_0}$ $\mathbf{c_{k,l}}$, where $(\mathbf{k},l) \in \mathbf{A_{ij}}$. Equation (2.4) can be re-written, when $\mathbf{g} = \mathbf{h}$, so that the $\mathbf{c_{ij}}$'s are written directly in terms of the $\mathbf{c_{k,l}}$'s. If $\mathbf{g} = \mathbf{h}$, we write $\mathbf{c_{ij}}$ as $\mathbf{c_{i+j}}$, and observe that (2.4) takes the form

(2.5)
$$\mathbf{e}_{\underline{i}} = (\mathbf{I} - \mathbf{G}_{0})^{-1} \{ \mathbf{g}^{\underline{i}} + \sum_{k=1}^{\underline{i}-1} {i \choose k} (\mathbf{g}^{\underline{i}-k} \circ \mathbf{G}_{0} \mathbf{e}_{k}) \}, \quad 1 \leq \underline{i} \leq n.$$

Recall also that from (2.2), $\mathbf{c}_0 \equiv 1$. We claim that the system (2.5) can be re-written as

(2.6)
$$\mathbf{e}_{\mathbf{i}} = (\mathbf{I} - \mathbf{e}_{\mathbf{0}})^{-1} \{ \sum_{k=1}^{\mathbf{i}} (-1)^{k+1} {i \choose k} \ \mathbf{g}^{k} \circ \mathbf{e}_{\mathbf{i}-k} \}, \quad 1 \leq i \leq n.$$

The proof is by induction. For n = 1, the result is obvious, so suppose (2.5) and (2.6) are equivalent systems for n = m. To check the (m+1)'st equation in the (m+1)'st system, observe that a solution of (2.5) satisfies

(2.7)
$$\mathbf{c}_{m+1} = (\mathbf{I} - \mathbf{c}_0)^{-1} \{ \mathbf{g}^{m+1} + \sum_{i=1}^{m} {m+1 \choose i} (\mathbf{g}^{m+1-i} \circ \mathbf{c}_0 \ \mathbf{c}_i) \}$$

By the inductive hypothesis, (2.6) shows that

(2.8)
$$\mathbf{G}_0 \mathbf{e}_i = -\sum_{k=0}^{i} (-1)^{k+1} \binom{i}{k} \mathbf{g}^k \circ \mathbf{e}_{i-k}$$

for $i \leq m$. Substituting (2.8) into (2.7), we get that $(\mathbf{I} - \mathbf{G}_0)\mathbf{c}_{m+1}$ equals

$$g^{m+1} + \sum_{i=1}^{m} \sum_{k=0}^{i} {m+1 \choose i} {i \choose k} {(-1)}^{i-k} g^{m+1-k} \circ e_k$$

$$= \sum_{k=0}^{m} {m+1 \choose k} (g^{m+1-k} \circ e_k) \sum_{j=1}^{m+1-k} {m+1-k \choose j} (-1)^{m+1-k-j}$$

$$= \sum_{k=0}^{m} {m+1 \choose k} (g^{m+1-k} \circ e_k) (-1)^{m+2-k}$$

$$= \sum_{\ell=1}^{m+1} {m+1 \choose \ell} (g^{\ell} \circ e_{m+1-\ell})^{(-1)\ell+1} ,$$

which is equivalent to the (m+1)'st relation of (2.6) (the binomial identity was used for the third equality). The steps being reversible, this proves the claimed result. We remark that (2.6) yields the equations of [4] for i=1, 2.

3. Proof of the Theorem

We proceed via a series of lemmas.

(3.1) Lemma. If $b_{mn}(z) < \infty$, then the r.v.'s $Y(g)^{1} Y(h)^{j}$ are integrable under the probability distribution P_{x} for $0 \le i \le m$, $0 \le j \le n$, $x \in E$.

Proof. Note that

$$(Y(|g|) \vee 1)^{1} (Y(|h| \vee 1)^{j} \leq (Y(|g| \vee 1)^{m} (Y(|h| \vee 1)^{n})^{m})$$

so that $b_{ij}(z) < \infty$ for $0 \le i \le m$, $0 \le j \le n$. Since \mathbb{Z} is irreducible, it follows that $P_{\mathbb{Z}}\{T(y) < T(z)\} > 0$ for all $y \in \mathbb{E}$, for otherwise the regenerative property guarantees that $P_{\mathbb{Z}}\{T(y) = \infty\} = 1$, which violates our irreducibility assumption.

Then, by the strong Markov property applied at time T(y),

$$E_{z} \left\{ \left(\int_{T(y)}^{T(z)} |g(X(s)|ds \vee 1)^{i} \left(\int_{T(y)}^{T(z)} |h(X(s))|ds \vee 1 \right)^{j}; T(y) < T(z) \right\}$$

$$= b_{ij}(y) P\{T(y) < T(z) |X(0) = z\} \le b_{ij}(z)$$

so that $b_{ij}(y) < \infty$ for all $y \in E$, which proves the result. \square

(3.2) Proposition. If $b_{mn}(z) < \infty$, then $a_{ij}(x)$ exists and is finite for $0 \le i \le n$, $0 \le j \le n$, $x \in E$. Furthermore, A solves (2.2).

Proof. The first part follows immediately from Lemma 3.1. For the second part, the integrability of $Y(g)^{i} Y(h)^{j}$ ensures that the following manipulations of conditional expectations are valid:

$$\begin{split} \mathbf{a}_{i,j}(\mathbf{x}) &= \mathbb{E}_{\mathbf{x}} \{ \mathbf{Y}(\mathbf{g})^{1} \ \mathbf{Y}(\mathbf{h})^{j} \} \\ &= \mathbb{E}_{\mathbf{x}} \{ \mathbf{Y}(\mathbf{g})^{1} \ \mathbf{Y}(\mathbf{h})^{j} ; \ \tau = 1 \} + \mathbb{E}_{\mathbf{x}} \{ \mathbf{Y}(\mathbf{g})^{1} \ \mathbf{Y}(\mathbf{h})^{j} ; \ \tau > 1 \} \\ &= \mathbf{g}^{1}(\mathbf{x}) \ \mathbf{h}^{j}(\mathbf{x}) \ \boldsymbol{\mu}_{i+j}(\mathbf{x}, \mathbf{z}) \ \mathbf{p}_{\mathbf{x}\mathbf{z}} \\ &+ \mathbb{E}_{\mathbf{x}} \big\{ (\mathbf{g}(\mathbf{R}_{0}) \ \boldsymbol{\alpha}_{0} + \int_{\mathbf{S}_{1}}^{\mathbf{T}(\mathbf{z})} \mathbf{g}(\mathbf{X}(\mathbf{t})) \mathbf{d}\mathbf{t})^{1} \ (\mathbf{h}(\mathbf{R}_{0}) \ \boldsymbol{\alpha}_{0} \\ &+ \int_{\mathbf{S}_{1}}^{\mathbf{T}(\mathbf{z})} \mathbf{h}(\mathbf{X}(\mathbf{t})) \mathbf{d}\mathbf{t})^{j} ; \ \tau > 1 \big\} \\ &= \mathbf{g}^{1}(\mathbf{x}) \ \mathbf{h}^{j}(\mathbf{x}) \ \boldsymbol{\mu}_{i+j}(\mathbf{x}, \mathbf{z}) \ \mathbf{p}_{\mathbf{x}\mathbf{z}} \\ &+ \frac{1}{k=0} \sum_{\ell=0}^{j} (\frac{1}{k}) (\frac{1}{\ell}) \ \mathbb{E}_{\mathbf{x}} \big\{ \mathbf{g}(\mathbf{R}_{0})^{1-k} \ \mathbf{h}(\mathbf{R}_{0})^{j-\ell} \ \boldsymbol{\alpha}_{0}^{i+j-k-\ell} \big(\int_{\mathbf{S}_{1}}^{\mathbf{T}(\mathbf{z})} \mathbf{g}(\mathbf{X}(\mathbf{t})) \mathbf{d}\mathbf{t} \big)^{k} \\ &\cdot (\int_{\mathbf{S}_{1}}^{\mathbf{T}} \mathbf{h}(\mathbf{X}(\mathbf{t})) \mathbf{d}\mathbf{t} \big)^{\ell} ; \ \tau > 1 \big\} \\ &= \mathbf{g}^{i}(\mathbf{x}) \ \mathbf{h}^{j}(\mathbf{x}) \ \boldsymbol{\mu}_{i+j}(\mathbf{x}, \mathbf{z}) \ \mathbf{p}_{\mathbf{x}\mathbf{z}} \\ &+ \frac{1}{k=0} \sum_{\ell=0}^{j} (\frac{1}{k}) (\frac{1}{\ell}) \ \mathbf{g}^{i-k}(\mathbf{x}) \ \mathbf{h}(\mathbf{x})^{j-\ell} \sum_{\mathbf{y} \neq \mathbf{z}} \mathbf{p}_{\mathbf{x}\mathbf{y}} \ \boldsymbol{\mu}_{i+j-k-\ell}(\mathbf{x}, \mathbf{y}) \ \boldsymbol{\alpha}_{k,\ell}(\mathbf{y}) \\ &= (\mathbf{g}^{i} \ \mathbf{o} \ \mathbf{h}^{j} \ \mathbf{o} \ \mathbf{h}^{j}(\mathbf{x}) \ \mathbf{o} \ \mathbf{h}^{j}(\mathbf{x}) + \sum_{(\mathbf{k},\ell) \in \mathbf{B}_{i,j}} (\frac{1}{k}) (\frac{1}{\ell}) (\mathbf{g}^{i-k} \ \mathbf{o} \ \mathbf{h}^{j-\ell} \\ &\circ (\mathbf{G}_{i+i-k-\ell}, \mathbf{a}_{k,\ell})(\mathbf{x})) \ ; \end{split}$$

the strong Markov property at time S_1 was used to obtain the second last equality. \square

(3.3) Lemma. If $b_{mn}(z) < \infty$, then $A \in C_{mn}$.

Proof. For the absolute summability observe that $d_{ij}(x) = E_x\{Y(|g|)^i Y(|h|)^j\}$ satisfies

$$\begin{split} \mathbf{d}_{ij} &= |\mathbf{g}|^{1} \circ |\mathbf{h}|^{j} \circ \beta_{i+j} \\ &+ \sum_{(k,\ell) \in B_{ij}} {\binom{i}{k}} {\binom{j}{\ell}} {(|\mathbf{g}|^{i-k} \circ |\mathbf{h}|^{j-\ell} \circ (G_{i+j-k-\ell} d_{k\ell}))} \ . \end{split}$$

But $d_{ij}(x) \leq b_{ij}(x) < \infty$, so $|\mathbf{g}|^{i-k} \circ |\mathbf{h}|^{j-l} \circ (\mathbf{G}_{i+j-k-l} \mathbf{d}_{kl})$ is finite, proving the first part, since $|\mathbf{a}_{ij}| \leq \mathbf{d}_{ij}$. For the second,

$$(G_0^k a_{ij})(x) = E_x \{ (\int_{S_k}^{T(z)} Y(g))^i (\int_{S_k}^{T(z)} Y(h))^j; \tau > k \},$$

which tends to zero by integrability of $Y(|g|)^{i} Y(|h|)^{j}$.

(3.4) Lemma. If $b_{min}(z) < \infty$, then A is the unique solution to (2.2) in \mathcal{C}_{min} .

Proof. Suppose that $\{a_{rs}: 0 \le r \le k, 0 \le s \le l\}$ is unique in C_{kl} for $k+l \le i+j$, where $0 \le i \le m$, $0 \le j \le n$. We shall prove uniqueness in C_{ij} ; "bootstrapping" this result yields the lemma. Since the a_{rs} 's are unique in C_{kl} , any solution to the (i,j) equation must satisfy

(3.5)
$$\mathbf{e}_{ij} = \mathbf{g}^{i} \circ \mathbf{h}^{j} \circ \boldsymbol{\beta}_{i+j} + \sum_{(k,l) \in A_{ij}} (\frac{i}{k}) (\frac{j}{l}) (\mathbf{g}^{i-k} \circ \mathbf{h}^{j-l} \circ \mathbf{G}_{i+j-k-l} \mathbf{a}_{k,l}) + \mathbf{G}_{0} \mathbf{e}_{ij}$$

By the absolute summability, any two solutions $\mathbf{c_{ij}}$, $\mathbf{c_{ij}'}$ of (3.5) must satisfy $(\mathbf{c_{ij}} - \mathbf{c_{ij}'}) = \mathbf{G_0}(\mathbf{c_{ij}} - \mathbf{c_{ij}'})$. Since $\mathbf{G_0^k}(\mathbf{c_{ij}} - \mathbf{c_{ij}'}) > 0$ as $\mathbf{k} + \infty$, it follows that $\mathbf{c_{ij}} = \mathbf{c_{ij}'}$, proving uniqueness in \mathcal{C}_{ij} .

These above results prove all the assertions of the theorem.

Acknowledgment

Both authors gratefully acknowledge support by U.S. Army Research Office Contract DAAG29-84-K-0030. The second author was also partially supported by National Science Foundation Grant MCS-8203483.

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4. TITLE (and Substitle) RECURSIVE MOMENT FORMULAS FOR REGENERATIVE SIMULATION		5. Type of REPORT & PERIOD COVERED TECHNICAL REPORT
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s)		8. CONTRACT OR GRANT NUMBER(*)
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DEPARTMENT OF OPERATIONS RESEARCH STANFORD UNIVERSITY STANFORD, CA 94305		19. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME AND ADDRESS U. S. Army Research Office Post Office Box 12211 Research Triangle Park NC 27709		OCTOBER 1984
		13. NUMBER OF PAGES
14. MONITORING AGENCY NAME & ADDRESS(If different from Controlling Office)		15. SECURITY CLASS. (of this report)
		Unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

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17. DISTRIBUTION STATEMENT (of the abstract entered in Black 20, If different from Report)

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REGENERATIVE SIMULATION, SEMI-MARKOV PROCESS, RECURSIVE MOMENT FORMULAS

romy and identify by block number)

ABSTRACT: Let $\mathbf{Z} = \{X(t), : t > 0\}$ be a regenerative semi-Markov process with countable state space E and f a real-valued function on E. Denote by $Y_1(f)$ the area under the function $f(X(\bullet))$ in the first regenerative cycle. This paper gives a recursive method for computing moments of the form $E\{Y_1^n(f)Y_1^n(g)\}$ for arbitrary f and g, and m, $n \ge 1$. These moments are needed to improve the accuracy of confidence intervals for steady state parameters obtained when using the method of regenerative simulation.

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